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Evaluating ICA-Based Artifact Removal for EEG Motor Task Classification

Background

Electroencephalography (EEG) is widely used to monitor brain activity, especially for decoding motor imagery tasks in brain-computer interfaces (BCIs). However, EEG signals are noise-sensitive, with the electrodes picking up physiological and technical artifacts such as eye blinks, muscle movement, or electromagnetic interference (Cross Villasana, 2022). These artifacts can severely impact the accuracy of machine learning models trained to classify cognitive or motor states.

In this project, we apply Independent Component Analysis (ICA) to remove stereotyped artifacts from raw EEG signals and assess whether this improves the classification performance of motor imagery tasks. We use the PhysioNet EEG Motor Movement/Imagery Dataset (EEGMMIDB), which contains 64-channel EEG recordings from subjects performing imagined and real movements.

Dataset Description

The EEGMMIDB dataset from Physionet (Goldberger et al., 2000) includes 109 subjects who performed 14 experimental runs, including two one-minute baseline runs (one with eyes open, one with eyes closed) and three two-minute baseline tasks. Each EEG recording was preprocessed to extract events corresponding to motor imagery cues. For this project, only four subjects were selected due to the complexity and magnitude of EEG data. The dimensions are shown below:

Feature	Description
Number of subjects	4
Epochs	1392
Sampling rate	160 Hz (80 Nyquist)
Epoch duration	4.5 seconds (−0.5 to 4.0 sec)
Number of channels	64 (standard 10-20 montage)
Event classes	Rest, Left fist, Right fist, Feet
Runs	14

Figure 1. Data Summary

Algorithm: ICA

Independent Component Analysis (ICA) is an unsupervised learning algorithm that separates a multivariate signal into statistically independent, non-Gaussian source components. It is instrumental in blind source separation problems — such as separating brain signals from artifacts in EEG data — where we only observe mixtures but have no information regarding the original sources (Talebi, 2021). For ICA to work, there are three critical assumptions about the data and how EEG might handle them:

1. The sources must be statistically independent
   - ⇒ EEG channels come from different anatomical sources and are temporally uncorrelated.
2. The components must be non-Gaussian
   - ⇒ Brain signals and artifacts tend to be sparse, spiky, or heavy-tailed, unlike white noise
3. The combined symbols must be a linear mixture
   - ⇒ Electrodes record linear mixtures of multiple sources (brain activity, muscle activity, eye blinks)

In relation to EEG analysis, motions such as eyeblinks or chewing are considered artifacts, and the hope is that ICA can be used to isolate only the neural activity from the collected signals and improve the classification of the motor tasks given to the subjects.

Mathematically, ICA assumes the observed linear mixture of signals can be modeled as:

$$X = AS$$

where X is the original observed EEG signals, A is the unknown 'mixing matrix,' and S is the independent sources. ICA aims to simultaneously estimate $A^{-1} \approx W$ (the 'unmixing matrix') and S such that $U = WX$. It does so by tweaking W until the recovered sources U ideally match the original sources S and $A^{-1}W \approx I$.

ICA Demonstration

To remove an artifact, it is common for clinicians to manually annotate each signal and remove the corresponding independent component before reconstructing the data. The visualization below demonstrates an example of Subject 1 performing Task 3 (right movement), where red represents high neural activity and blue represents low activity. ICA00 and ICA01 correspond to the motion of blinking with high probabilities > 0.8, whereas ICA13 maximally represents likely muscle activity with highest probability (Delorme, A et al., n.d.). These components would be removed from the data as a preprocessing step to keep only brain activity components before downstream classification.

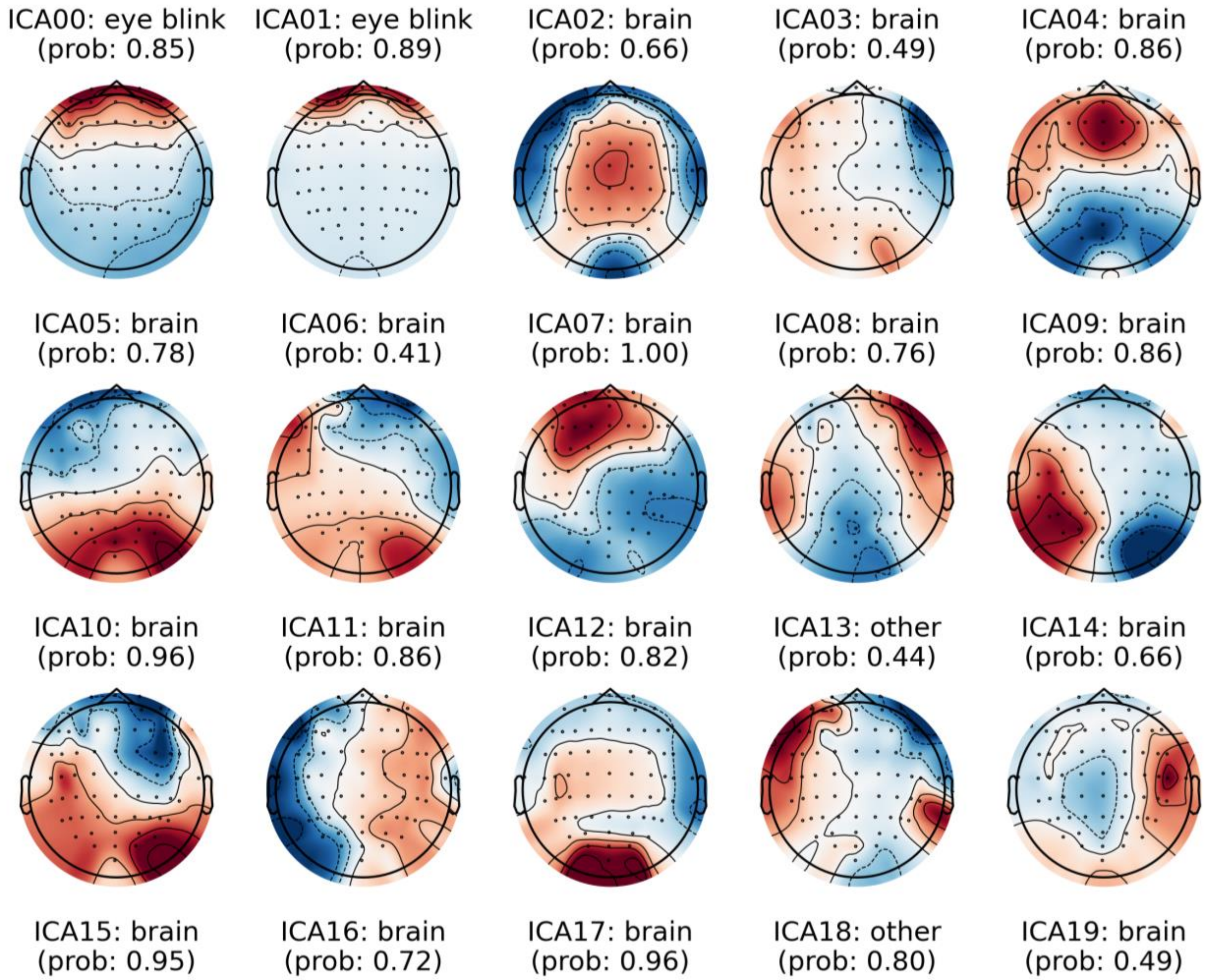

Figure 2. Spatial Topography of Independent Components

Since it is labor-intensive to manually remove all the artifacts in each signal (even if it is the Gold Standard), the open source MNE package handles EEG data preprocessing techniques to automate artifact (eye, muscle, heart, line noise, and channel noise) detection and removal through ICA infomax. The number of components selected as the parameter was the number of principal components needed to explain 99% of the variation in the data. Feature extraction techniques using scipy were employed to capture time, frequency, joint time-frequency, and spatial domains (Rabha, J., n.d.). The data were concatenated to include Frequency-domain (PSD), Short-Time Fourier Transform (STFT), Hjorth parameters (signal variation), Skewness & Kurtosis (distribution shape), and Common Spatial Patterns (CSP).

Classification Algorithms and Results

The classification performances on the raw vs. ICA-cleaned EEG signals were evaluated on three models. A Random Forest Model and Multilayer Perceptron Model were fitted using hyperparameter tuning (GridSearch) and 5-fold cross-validation. Then, a compact CNN called EEGNet (Lawhern et al., 2018) specifically designed to classify EEG based BCI data was repurposed for comparison. EEGNet architecture includes stages for temporal convolution (learns frequency filter), spatial convolution (learns spatial patterns across channels for motor cortex areas), and separable convolution (combine both features). Its compact design requires very few parameters compared to other deep learning networks (~2600 parameters). The model performances are shown below:

Data	Model	Hyperparameters	Accuracy
Raw EEG	Random Forest	estimators: 100; min_sample_split : 2, min_sample_leaf: 2; max_depth: 10	0.624
ICA Cleaned	Random Forest	estimators: 200, min_samples_split: 5, min_samples_leaf: 4; max_depth: 10}	0.609
Raw EEG	MLP	max iterations: 200; lr: 0.001; hidden layer size: 100; activation: ReLU	0.661
ICA Cleaned	MLP	max iterations: 400; lr: 0.001; hidden layer size: 5; activation: ReLU	0.667
Raw EEG	EEGNet	activation: ELU; optimizer: Adam; lr=0.001; weight decay: 1e-4; epochs: 50	**0.707**
ICA Cleaned	EEGNet	activation: ELU; optimizer: Adam; lr=0.001; weight decay: 1e-4; epochs: 31	**0.684**

Figure 3. Performance Evaluation

Despite the data taken from only 4 subjects, we observe from Figure 3 that the overall classification accuracies were relatively decent, ranging from ~0.6-0.71. The Random Forest model performed the worst out of the three models, while the Multilayer Perceptron model did only slightly better. As expected, the EEGNet performed the best but only marginally. The results make sense, as the Rando Forest and MLP typically rely on the manually extracted features for classification, while EEGNet learns optimal features from the raw data. Unfortunately, no substantial evidence was found in support of using ICA to remove artifacts before classification tasks. From rigorous testing (even on different datasets), a notably increase in performance using ICA was very scarce, and often, using ICA decreased the performances of the classification models.

Discussion

The reasons ICA was not shown to improve performances could be attributed to the small sample size of subjects that was used to test the data on to compromise computational efficiency. The Random Forest took around 4 minutes to execute, while the MLP took 11, and EEGNet took 14 minutes. There was severe class imbalance, with most epochs annotated as Class 1 (Rest/Baseline phase). This imbalance particularly affects traditional machine learning algorithms like Random Forest, which tend to bias toward the majority class, potentially masking the true effect of ICA preprocessing on minority classes representing actual motor imagery tasks. Additionally, since an automated ICLabel function was used to remove artifacts using ICA, it is likely that the algorithm might have been too rigorous in removing components that were necessary to explain the task-relevant neural signals in the data. Manual inspection of removed components would have provided better interpretability but was computationally prohibitive for this dataset size. The performance of EEGNet (70.7% accuracy) compared to traditional methods aligns with recent literature showing that domain-specific deep learning architectures can inherently handle noisy EEG data through built-in regularization mechanisms (dropout, batch normalization), potentially making aggressive preprocessing less critical. We note that the cleaned ICA data always converged quicker than the raw data for EEGNet, making it more efficient while compromising very little accuracy.

Overall, while this project did not find strong evidence that ICA improves classification accuracy in this setting, the ICA algorithm and its theoretical applications remain under-researched and still hold much potential to be explored in the realm of EEG analysis, fMRIs, and possibly imaging.

References

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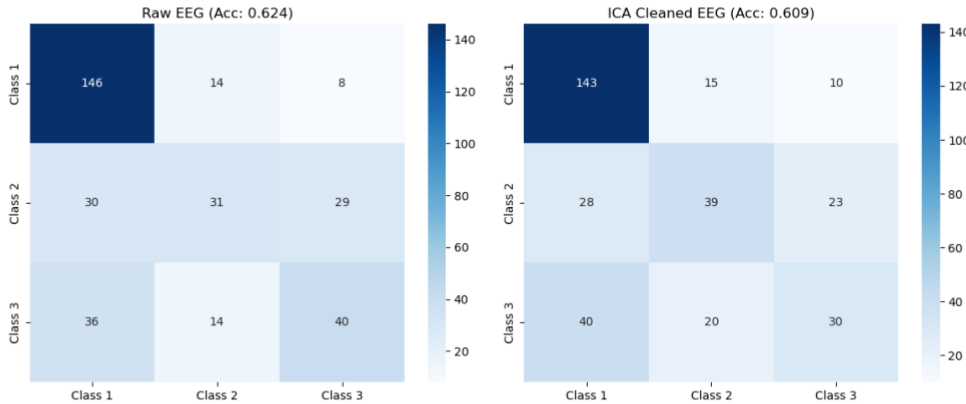
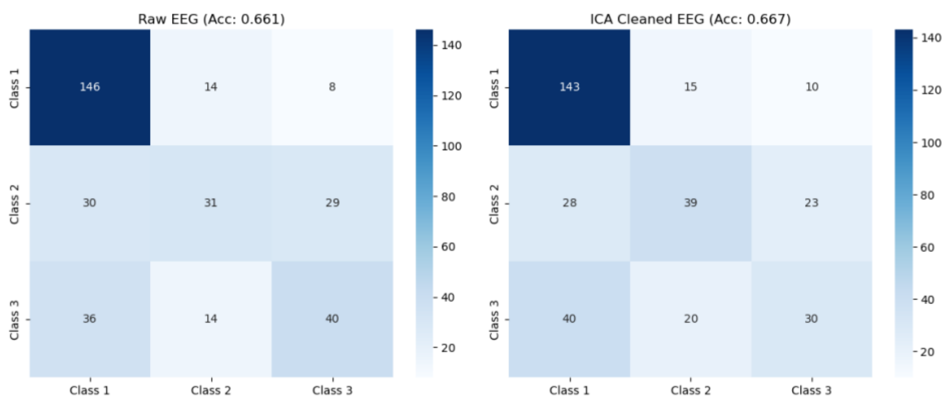
Supplementary Materials

Random Forest Classifier Confusion Matrix:



MLP Confusion Matrix:



EEGNet Confusion Matrix: